Deep learning application in diverse fields with plant weed detection as a case study

Uchechi F. Ukaegbu
Department of Mechanical & Industrial Engineering
University of Johannesburg
Johannesburg, South Africa
ukaegbuuchechi531@gmail.com

Lagouge K. Tartibu
Department of Mechanical & Industrial Engineering
University of Johannesburg
Johannesburg, South Africa
ltatibu@uj.ac.za

Modestus O. Okwu
Department of Mechanical & Industrial Engineering
University of Johannesburg
Johannesburg, South Africa
okwu.okechukwu@fupre.edu.ng

Isaac O. Olayode
Department of Mechanical & Industrial Engineering
University of Johannesburg
Johannesburg, South Africa
olayode89@gmail.com

Abstract

Machine learning applications have gained popularity over the years as more advanced algorithms like the deep learning (DL) algorithm are being employed in signal identification, classification and detection of cracks or faults in structures. The DL algorithm has broader applications compared to other machine learning systems and it is a creative algorithm capable of processing data, creating pattern, interpreting information due to its high level of accuracy in pattern recognition under stochastic conditions. This research gives an exposition of DL in diverse areas of operations with a focus on plant weed detection which is inspired by the need to treat a specific class of weed with a particular herbicide. A Convolutional Neural Network (CNN) model was trained through transfer learning on a pre-trained ResNet50 model and the performance was evaluated using a random forest (RF) classifier, the trained model was deployed on a raspberry pi for prediction of the test data. Training accuracies of 99% and 93% were obtained for the CNN and RF classifier respectively. Some recommendations have been proffered to improve inference time such as the use of better embedded systems such as the Nvidia Jetson TX2, synchronizing DL hardware accelerators with appropriate optimization techniques. A prospect of this work would be to incorporate an embedded system, deployed with DL algorithms, on an unmanned aerial vehicle or ground vehicle. Overall, it is revealed from this study that DL is highly efficient in every sector and can improve the accuracy on automatic detection of systems in especially in this era of Industry 4.0.

CCS Concepts: • **Computing methodologies → Artificial Intelligence → Computer Vision**.

Keywords: Deep learning algorithm, Random forest, Convolutional neural network, fourth industrial revolution, Agriculture

ACM Reference Format:
Uchechi F. Ukaegbu, Lagouge K. Tartibu, Modestus O. Okwu, and Isaac O. Olayode. 2021. Deep learning application in diverse fields with plant weed detection as a case study. In *International Conference on Artificial Intelligence and its Applications (icARTi '21), December 9–10, 2021, Virtual Event, Mauritius.* ACM, New York, NY, USA, 9 pages. https://doi.org/10.1145/3487923.3487926

Permission to make digital or hard copies of all or part of this work for personal or classroom use is granted without fee provided that copies are not made or distributed for profit or commercial advantage and that copies bear this notice and the full citation on the first page. Copyrights for components of this work owned by others than ACM must be honored. Abstracting with credit is permitted. To copy otherwise, or republish, to post on servers or to redistribute to lists, requires prior specific permission and/or a fee. Request permissions from permissions@acm.org.
icARTi '21, December 9–10, 2021, Virtual Event, Mauritius
© 2021 Association for Computing Machinery.
ACM ISBN 978-1-4503-8575-6/21/12...$15.00
https://doi.org/10.1145/3487923.3487926

1 Introduction

The application of deep learning (DL) in solving real life problems has stirred a great deal of recognition with significant impacts made in areas such as cancer prognosis[43], image analysis[6], self-driving cars[46], speech recognition[21], natural language processing[20] and prediction of natural disasters[45], and others. These advancements were believed to have been initiated by Hinton, Osindero and Tey [23] who introduced the concepts of layer-wise greedy-learning and deep belief networks. DL's ability to analyze big data, automatically extract features and its short testing times have made it an undoubtable preference to other conventional machine learning methods [34]. However, it is computationally intensive requiring long training times but thanks to the high processing speed and parallelism of DL hardware accelerators which has greatly ameliorated this drawback [36].

Deep learning can be defined as a subset of machine learning, consisting of multi-processing layers, which transforms and learns data representations with various features in a hierarchical manner [29]. It is made up of the input, several hidden and output layers with nodes in each layer connected to nodes in the corresponding layer thus mimicking the neuron structure of the human brain [38]. A weighted sum of the input is transformed by an activation function which generates non-linear outputs fed as input to the adjacent units of the succeeding layer until it reaches the output layer [55]. The forward and back propagation procedures are iterated until the weights and biases are optimized and then the result of the output layer becomes the solution to the problem. The activation functions mostly used are the sigmoid, hyperbolic tangent(tanh), Rectified Leaky Unit (ReLU) and Identity functions because they make it easier to compute the loss function required for weight optimization [49, 74]. DL architectures are classified into supervised, semi-supervised and un-supervised learning models. In supervised learning, the dataset used during the training procedure is fully labelled which is in contrast to unsupervised learning where features are extracted from unlabeled data. However, Semi-supervised leaning incorporates the functionalities of the aforementioned learning models whereby the training data is made up of both labelled and unlabeled datasets. Furthermore, DL architectures can be categorized as either discriminative which generally aligns with supervised learning models or generative which aligns with unsupervised learning models [41].

2 Generative DL Architectures

2.1 Auto-encoder (AE)

This is a neural network which consists of the input, hidden and output layers. In this architecture, input data is transformed using unsupervised learning to an abstract form in a lower dimension and then reconstructed to produce output by fine-tuning with backpropagation [57]. Dimension reduction and input reconstruction are carried out by encoder and decoder blocks with the aim of generating outputs which are as similar as possible to the input. AE is advantageous because it facilitates the extraction of relevant features and due to the fact that the learning efficiency is improved as the input data is converted to a representation in a lower dimension [71].

2.2 Restricted Boltzman Machines (RBM)

This is a type of the artificial neural network (ANN) which consists of the visible and hidden layers with each neuron connected to all units in the adjacent layer but with is no connectivity within the same layer. This architecture uses unsupervised learning to build an RBM structure which probabilistically reconstructs the input [57]. Also, variants of the RBM were proposed to boost dimensionality reduction, collaborative filtering and feature extraction functions. They are the discriminative RBM, conditional RBM and FE-RBM introduced by Larochellle and Bengio [33], Mnih et al [39] and Elfwing [14] respectively.

2.3 Deep Belief Networks (DBN)

This is a kind of ANN (proposed by Geoffrey Hinton) designed by stacking several RBMs, consists of the visible layer which accepts the input and the hidden layers responsible for extracting features[42]. With the output of a preceding RBM used to train the next RBM layer, the training phases of a DBN is carried out in two stages: pre-training and fine-tuning stages [34, 47]. In pre-training stage, the DBN applies unsupervised learning process to extract features from the input data while in the fine-tuning stage, supervised learning using the backpropagation algorithm is used to modify the network parameters.

2.4 Generative Adversarial Network (GAN)

This is deep neural network (DNN) structure with two networks: The Generator and Discriminator. The generator produces synthesized data derived from a data distribution while a discriminator functions to discriminate between the true data distribution and the data from the generator. In order to attain optimization, the GAN is trained so that the generator produces data which is identical to the true distribution, so much that the discriminator has difficulty in differentiating between the true distribution and synthesized data [4].

3 Discriminative DL Architecture

3.1 Convolutional Neural Network (CNN)

This is a class of DNN inspired by the human visual mechanism and capable of extracting hierarchical features from a two-dimensional input (image, text or audio signal) using a sequence of layers. It consists of the input, convolutional, pooling, fully connected and output layers. The CNN is widely used for computer vision applications involving image and video recognition due to its sparse interaction, equivalent representation as well as its weight capabilities [51]. The convolutional layer consists of a set of kernels (arrays of weights) which extract features (edges, contours, strokes, textures, orientation, color, etc.) from an input data. These kernels are convoluted on the image by computing the sum of their dot products to generate feature maps. An activation function (most commonly the ReLU) is applied to introduce non-linearity and prevent network saturation [50]. The pooling layer, which is either a max or average pooling function, reduces the spatial dimensions of the feature map and computation load in the network while retaining relevant information [26]. Thereafter, the fully connected layer performs the classification tasks to produce list of probable outputs and then passed through a softmax function which selects the output with the highest probability as the prediction for a given input. Similar to a conventional neural network, the goal of a CNN is to optimize the loss function in a network and it achieves this by applying backpropagation algorithm via gradient descent to train the kernels and modify the weights. Fig. 1. shows the architecture of the CNN adapted from [56].

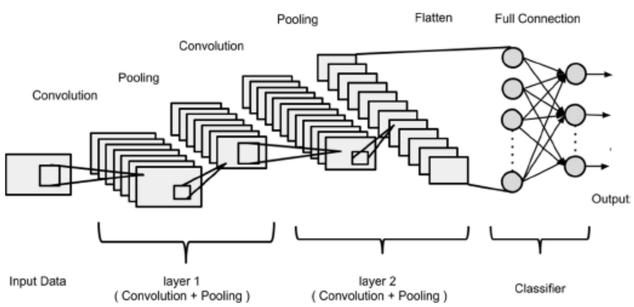

Figure 1. Convolutional Neural Network Architecture

3.2 Recurrent Neural Network (RNN)

This is a kind of DNN consisting of the input, hidden and output layers applied in language modelling, machine translation, speech recognition, etc. [42, 69]. It is used to model sequential information and possesses an internal memory which captures information about previous computations. It takes in two inputs (the present and recent past inputs) and applies the backpropagation through time (BPTT) algorithm for training the network such that the output at time step 't' is dependent on the output at time step 't-1'[47, 61].

3.3 Long Short-Term Memory (LSTM)

This is a special variant of the RNN which was proposed to make up for the drawback in RNN such as sensitivity to change in parameter, vanishing and exploding gradient. It consists of the input, hidden as well as the output layers and used for applications involving long dependencies in time such as handwriting generation, video descriptor, etc. The hidden layer of the LSTM comprises the **memory cell** (which captures information for a certain time-frame and **gates** (input, forget and output gates). The input gate determines the new formation to be stored in the LSTM cell, the forget gate decides on which information should be forgotten and the output gate controls flow if information to the network [42, 56].

3.4 Transfer Learning

Transfer learning could be defined as the ability to adopt previously acquired knowledge to new applications which have similar attributes. It improves model performance and prevents over-fitting especially in a situation of training data deficit as it makes use of weights from pre-trained models [30]. According to Coulibay et al [12], transfer learning could either be by deep feature extraction or fine-tuning. The ResNet [21], VGGNet [59], MobileNet [25], GoogleNet [60], etc. are valid examples of pre-trained models. Also, DNN architectures are implemented on frameworks such as Tensorflow [3], Theano [2], Keras [15], Caffe [27], Pytorch [48], and others.

4 Deep Learning Applications in Diverse Fields

Deep learning algorithm is a very powerful algorithm useful in diverse areas of operation, ranging from the field of manufacturing for detection of defective products as well as detection of weld faults and cracks in structures; in healthcare DL is useful for medical diagnosis; in agriculture for weed detection; in banking sector for fraud detection; in entertainment; in marketing; in fast moving consumer goods; in education sector for detecting developmental delay in children; in natural language processing and many more. The applications are further expanded in this section.

4.1 Fraud Detection

Fraud, according to the Association of Certified Fraud Examiners, could be defined as the intentional misuse or misappropriation of an organization's assets for one's personal benefit. Technological advancements have given rise to a proliferation in fraudulent activities in areas of telecommunication, healthcare insurance, automobile insurance, credit card transactions, etc. [1]. Research has it that these illegitimate activities contribute to significant revenue loss and hence applying deep learning to detect such activities has to a large extent salvaged the situation [10, 31]. Zhang et al [75] proposed a homogeneity-oriented behavior analysis (HOBA) framework which exceptionally considered the geographical location of transactions. These variables were used to train DL models (DBN, RNN, and CNN) and were compared with traditional machine models (SVM, BPNN, RF). The DL models was observed to outperform the traditional machine learning methods and HOBA produced the best performance with the DBN model recording an accuracy, Area Under Curve (AUC) and Precision of 98.25%, 0.976 and 62.25% respectively. Chouiekh and Haj [10] proposed a fraud detection system for curbing the cunny intent of using and not paying for mobile communication services such as data subscription, voice calls, short message service (SMS), etc. Furthermore, in a bid to mitigate automobile insurance fraud, Wang and Xu [67] combined a Latent Dirichlet Allocation (LDA) frame work with a deep learning architecture. Data from the automobile insurance company and output from the LDA was used to train a DL model which gave a better accuracy of 91% when compared to that obtained from RF and SVM.

4.2 Healthcare

As we launch into the era of Industry 4.0, there seem to be a rapid advancement in the application of DL in a variety of task in the healthcare sector. These range from medical diagnosis, especially early analysis of life-threatening illnesses such as cancer [68], appendicitis [53] diabetes [54] to the solution procedures and prediction of future risks of such ailment. Although, it is still in its nascent stages, DL has good prospects of improving the technological situation in the medical domain. Coccia [11], with the intent of improving diagnosis and accelerate treatment of cancer, reviewed literatures which applied DL algorithms for the detection of lung and breast cancer. He concluded that DL proffers the opportunity to aid medical personnel in enhancing efficiency and making for a better prognosis. The authors in ref. [44] investigated on research works which applied DL to detect the Alzheimer's disease using structural and functional MRI scans. Also, Kalmet et al [28] carried out a survey on ways in which DL has been employed in detecting fracture using radiographs and computed tomography (CT). They also recommended that radionics, a method which extracts features of interest from medical images, be combined with DL to make for a more accurate classification. Lastly, a DL model for differentiating between the coronavirus pneumonia and influenza pneumonia using chest image was developed by Zhou et al [76].

4.3 Developmental Delay

It is a known fact that developmental disorders and speech issues will greatly affect the quality of life of children suffering from these problems. To address the situations, its calls for the application of deep learning in early diagnosis of these disorders which facilitates treatment. Yuan et al [70] proposed the use of a stacked sparse denoising Autoencoder (SSDA) to detect epileptic seizures in children. In the same vein, the authors in ref. [66] introduced a system for detecting speech disorders in children using an RNN. The RNN model was trained to learn the affinity and variance between the child's phone and correct phone in a measure of distance which is then used to train a binary classifier. This binary classifier gives a positive output if both phones are similar which signify the absence of speech disorder and vice versa. Shukla et al [58] proposed a system for the initial diagnosis of six developmental disorders (autism spectrum disorder, cerebral palsy, fetal alcohol spectrum syndrome, etc.) from facial images.

4.4 Digital Marketing

The world is currently witnessing a paradigm shift from analog to digital system, where every operation is going digital especially in the marketing sector. According to the American Marketing Association, digital marketing could be defined as a range of activities, accelerated by digital technologies, for generating and delivering value to customers. DL has the potentials to revolutionize the marketing industry with robust information on customer behavior, needs, preferences which can reduce production cost as well as increase profitability [52]. In the light of the above, Urban et al [65], investigated how DL could outdo statistical models in making complex marketing decisions by building a DL model to predict credit card choices for customers. This is sequel to the fact that DL uses several layers of variables, predicts its output through new data and can employ the use of verbal, numerical and visual inputs. In a bid to reduce the number of hours spent in manually locating video frames in a video scene where adverts could be added, Hossari et al [24] proposed the ADNet which automatically identifies billboard adverts.

4.5 Driverless cars

With the recent shift from third to fourth industrial revolution and high demand for technology of the future, the deep learning algorithm will play a major role in the improvement of self-driving cars. Data from sensors, cameras and mapping are used to create sophisticated models capable of navigating through traffic to effectively identify paths and signs using DL algorithms. Manikandan [37], applied DL to develop an automatic video annotation tool for a self-driving car. The proposed automatic annotation tool performed better than manual annotation with an accuracy as well as GPU processing time of 83% and 2.58minutes respectively. Also, the author in ref. [16] designed a self-driving car which utilized the Deep Q network consisting of three convolutional layers and four dense layers. Similarly, the Deepicar, an autonomous car, was developed by Bechlel et al [7]. Its principle of operation was such that input image from a camera is processed by a CNN model to produce an output of steering value angles which navigates the car.

4.6 Entertainment

In the area of entertainment, DL focuses on having a robust understanding of customer's behavior in systems and generating recommendations to help make better choices of products and services. Khan et al [32] proposed a movie tag extractor which extracts relevant information from a movie and represents it with tags that suitable explicates such movie. Movie tags extracted from a few movie trailers were used to train, through transfer learning, an Inception-v3 model on TensorFlow framework. Lund [35], on the other hand, introduced a movie recommender system which predicts the ratings of a user by gathering information from databases of ratings from other users. The movielen dataset was used to train an Autoencoder model on a Titan X GPU. The Deepstar model for detecting the main characters of a movie through extraction, face clustering and occurrence matrix generation was proposed by Haq et al [19].

4.7 Manufacturing Sector

In the domain of manufacturing, DL finds application in spotting weld faults, predicting properties and extent of degradation of mechanical components just to mention but a few. Recently, Zhang et al [72] presented a DL approach for the detection of porosity in welds during laser welding process. Also, Zhang et al [73] proposed an approach which tracks the degradation in air fact engines and predicts its remaining useful life using an LSTM model. Making use of performance degradation information of a high-pressure turbine only and some information from both high-pressure compressor and fan, the LSTM model was proved to surpass four other machine learning models.

4.8 Natural Language Processing (NLP)

DL is very useful in linguistics and semantics. The training process is such that human-like response and expression can be coded and processed to effectively build words, phrases and sentences. Hassan and Mahmood [20] proposed a joint model comprising the CNN and LSTM for the classification of sentences. This joint model was evaluated on the Stanford large movie review and Stanford sentiment Treebank datasets with accuracies of 93.3% and 89.2% obtained respectively, outperforming various existing approaches. The authors in ref. [8] applied DL approach in predicting the next alarm occurrence in an industrial plant. The Skip-Gram Negative Sampling (SGNS) model was used to convert the list of alarm time into vectors and this served as input to the LSTM network trained on TensorFlow framework for 100 epochs. Although the model was seen to be adversely affected by input data structure, tuning parameters, etc., it gave satisfactory results overall.

4.9 Application of DL in Agriculture

DL has met with much attention in the agricultural domain with applications in weed detection [62, 64], pest identification [9], disease classification [12], etc. Ferentinos [17] trained a set of CNN models to detect plant diseases using about 87800 image datasets. The training procedure was implemented on the Torch7 framework and deployed on a Graphical Processing Unit (GPU) of an Nvidia GTX 1080 card. Also, in ref. [5], banana plant disease detection was carried out on a LeNet model with about 3700 images. The black sigatoka, black speckle and healthy banana leaves were classified efficiently on deeplearning 4j framework. Dos Santos Ferreira et al [13] built a CNN model pretrained on the AlexNet model on a CaffeNet framework for detecting broadleaf and grass weeds in a soybean field. The results obtained were evaluated with Support Vector Machine (SVM), AdaBoost as well as Random forest and was seen to outperform them with an accuracy of about 99%.

5 Application of DL - Weed Detection in the Agricultural Sector as Case Study

Having looked at previous work done by researchers on the application of DL different sectors, a demonstration and experiment was conducted focusing on robotic weed control. Insight was taken from researches [22] which have shown that some species of weeds (such as grass) tend to be resistant to herbicides which are effective on other species (such as broadleaf). Hence a DL model has been applied to classify weeds (grass and broadleaf) and deploy same on a raspberry pi3. The targeted goals of this section include: (i) train a CNN model through transfer learning on a pretrained ResNet50 model and evaluate its performance using a random forest (RF) classifier; (ii) deploy the trained model on a raspberry pi for prediction of the test data.

5.1 Architecture of an Artificial Neural Network

The architecture of an artificial neuron, mathematical equations for loss function, gradient descent, activation functions are shown in Figure 2 and Equations 1-7.

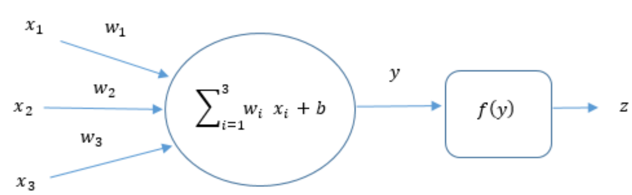

Figure 2. Structure of an Artificial Neuron

5.2 Notations and Formulations

$x_1, x_2, x_3 = Input\ Data,$
$w_1, w_2, w_3 = Weights,$
$b = bias$
$y = Weighted\ sum$
$z = output$
$T_i = True\ output\ of\ the\ i^{th}\ sample$
$Z_i = Estimated\ output\ of\ the\ i^{th}\ sample$
$m = Number\ of\ outputs\ generated$
$w_i = Weight\ of\ the\ i^{th}\ sample$
$Y = Learning\ rate$
$b_i = Bias\ of\ the\ i^{th}\ sample$
The Mathematical equations for the system are stated thus:

$$L = \frac{1}{2m} \sum_{i=1}^{m} (T_i - Z_i)^2 \tag{1}$$

$$w_i \rightarrow w_i - \gamma \frac{dL}{dw_i} \tag{2}$$

$$b_i \rightarrow b_i - \gamma \frac{dL}{db_i} \tag{3}$$

$$Sigmoid(y) = \frac{1}{1 + e^{-y}} \tag{4}$$

$$Tanh(y) = \frac{1 - e^{-2y}}{1 + e^{-2y}} \quad (5)$$

$$ReLU(y) = \{0, y\} \quad (6)$$

$$Identity(y) = y \quad (7)$$

Equation 4 -7: Commonly used activation functions in DL

5.3 Methodology

The datasets from the work of [13] were obtained from a public dataset source, Kaggle. They were divided into ratio of 5:3:2 for training, validation and testing respectively. A total of 5349 images comprising soybean, grass weed and broadleaf images with input shape of 224×224×3 and a batch size of 20 were used to train through transfer learning a CNN model. The ResNet50 model was the CNN model selected and evaluated with the RF classifier which according to Fernandez-Delgado et al [18] is the best machine learning classifier. The categorical cross-entropy loss function was used during training and the softmax function was applied to the output layer. By applying transfer learning, the last fully connected layer of the ResNet50 architecture was modified to a 3-neuron fully connected layer. The model was trained on the keras application programming interface, topmost of TensorFlow framework for 10 epochs.

5.4 Result and Discussion

After the training procedure which lasted for about 10 hours on a 4GB RAM Intel Core B160 Processor, accuracies of 99% and 93% were obtained for the CNN and RF classifier respectively as shown in Fig. 3 below. In the confusion matrix shown in Fig. 4, the highest and least accuracy was obtained for soybean and grass weed respectively with the CNN model while for the RF classifier, broadleaf weed had the least accuracy. Also, from the confusion matrix for the RF classifier, 34 images of grass weeds were confused for broadleaf and 20 images of the broadleaf class were confused for grass weed. However, for the CNN model, no weed class was confused for another.

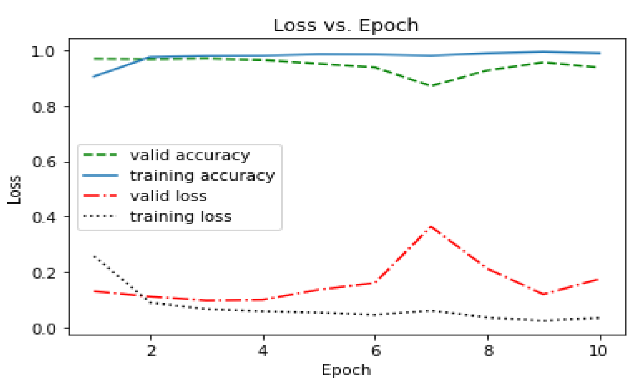

Figure 3. Graph of Accuracy/Loss Vs Epoch for the CNN model

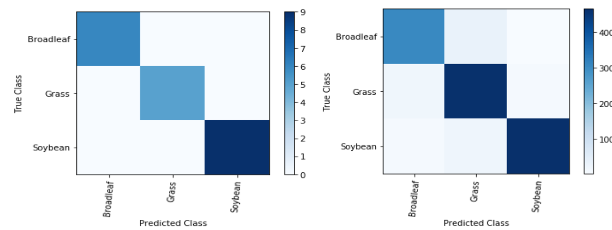

Figure 4. (a) Confusion matrix for the CNN model (b) Confusion Matrix for the RF classifier

The better performing model (CNN model) was deployed on the raspberry pi 3 to carry out prediction of the test data. Also, different light emitting diodes (LEDs) were lighted up immediately a broadleaf or grass weed was predicted as shown in Figure 5. This would be applied to the future work proposed to spray a particular herbicide on a grass weed and a different one on a broadleaf.

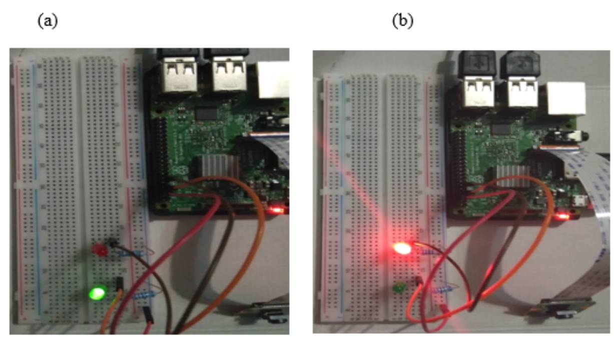

Figure 5. (a) Green LED lit when a broadleaf weed was predicted (b) Red LED lit when grass weed was predicted

6 Conclusion

This article is an elucidation of the application of Deep Learning in diverse field of operations. About ten areas of application of deep learning have been revealed in this research. In this era of fourth industrial revolution, information gathering, interpretation and analysis using deep learning algorithm will help in accurate recognition of patterns at higher level under uncertainties. Different areas of applications of DL has been discussed, ranging from industries, health care, agriculture, education and others. A case study was further presented on the application of deep learning in the agricultural sector. It is recommended that a more sophisticated embedded system such as the Nvidia Jetson Tx2 should be employed in future research. Also, combining DL hardware accelerators with appropriate optimization techniques would further reduce inference times as proposed in ref. [63]. Also, an embedded system, with DL deployed, can be incorporated to aerial vehicle to carry out real-time detection of weeds and selectively spray a particular herbicide on a specific class of weed.

Acknowledgments

The authors would like to thank the University of Johannesburg Research Committee and the Global Excellence and Stature (GES) scholarship board for their support towards the realization of this research work. Prof. Daddy Hezekiah (the International Mayor of Peace) and Engr. Prof. Chigbo Mgbemene are also specially appreciated for their mentorship and support towards the actualization of this goal. Dos Santos Ferreira, et al. [13] are highly appreciated for making their weed dataset publicly available.

References

[1] Aisha Abdallah, Mohd Aizaini Maarof, and Anazida Zainal. 2016. Fraud detection system: A survey. *Journal of Network and Computer Applications* 68 (2016), 90–113.

[2] Rami Al-Rfou, Guillaume Alain, Amjad Almahairi, Christof Angermueller, Dzmitry Bahdanau, Nicolas Ballas, Frédéric Bastien, Justin Bayer, Anatoly Belikov, Alexander Belopolsky, et al. 2016. Theano: A Python framework for fast computation of mathematical expressions. *arXiv e-prints* (2016), arXiv–1605.

[3] JJ Allaire, Dirk Eddelbuettel, Nick Golding, and Yuan Tang. 2016. TensorFlow for R.

[4] Mohamed Ahzam Amanullah, Riyaz Ahamed Ariyaluran Habeeb, Fariza Hanum Nasaruddin, Abdullah Gani, Ejaz Ahmed, Abdul Salam Mohamed Nainar, Nazihah Md Akim, and Muhammad Imran. 2020. Deep learning and big data technologies for IoT security. *Computer Communications* 151 (2020), 495–517.

[5] Jihen Amara, Bassem Bouaziz, and Alsayed Algergawy. 2017. A deep learning-based approach for banana leaf diseases classification. *Datenbanksysteme für Business, Technologie und Web (BTW 2017)-Workshopband* (2017).

[6] Szilárd Aradi. 2020. Survey of deep reinforcement learning for motion planning of autonomous vehicles. *IEEE Transactions on Intelligent Transportation Systems* (2020).

[7] Michael G Bechtel, Elise McEllhiney, Minje Kim, and Heechul Yun. 2018. Deeppicar: A low-cost deep neural network-based autonomous car. In *2018 IEEE 24th international conference on embedded and real-time computing systems and applications (RTCSA)*. IEEE, 11–21.

[8] Shuang Cai, Ahmet Palazoglu, Laibin Zhang, and Jinqiu Hu. 2019. Process alarm prediction using deep learning and word embedding methods. *ISA transactions* 85 (2019), 274–283.

[9] Xi Cheng, Youhua Zhang, Yiqiong Chen, Yunzhi Wu, and Yi Yue. 2017. Pest identification via deep residual learning in complex background. *Computers and Electronics in Agriculture* 141 (2017), 351–356.

[10] Alae Chouiekh and EL Hassane Ibn EL Haj. 2018. Convnets for fraud detection analysis. *Procedia Computer Science* 127 (2018), 133–138.

[11] Mario Coccia. 2020. Deep learning technology for improving cancer care in society: New directions in cancer imaging driven by artificial intelligence. *Technology in Society* 60 (2020), 101198.

[12] Solemane Coulibaly, Bernard Kamsu-Foguem, Dantouma Kamissoko, and Daouda Traore. 2019. Deep neural networks with transfer learning in millet crop images. *Computers in Industry* 108 (2019), 115–120.

[13] Alessandro dos Santos Ferreira, Daniel Matte Freitas, Gercina Gonçalves da Silva, Hemerson Pistori, and Marcelo Theophilo Folhes. 2017. Weed detection in soybean crops using ConvNets. *Computers and Electronics in Agriculture* 143 (2017), 314–324.

[14] Stefan Elfwing, Eiji Uchibe, and Kenji Doya. 2015. Expected energy-based restricted Boltzmann machine for classification. *Neural networks* 64 (2015), 29–38.

[15] François Chollet et al. 2015. keras, GitHub. https://github.com/fchollet/keras

[16] Abdur R Fayjie, Sabir Hossain, Doukhi Oualid, and Deok-Jin Lee. 2018. Driverless car: Autonomous driving using deep reinforcement learning in urban environment. In *2018 15th International Conference on Ubiquitous Robots (UR)*. IEEE, 896–901.

[17] Konstantinos P Ferentinos. 2018. Deep learning models for plant disease detection and diagnosis. *Computers and Electronics in Agriculture* 145 (2018), 311–318.

[18] Manuel Fernández-Delgado, Eva Cernadas, Senén Barro, and Dinani Amorim. 2014. Do we need hundreds of classifiers to solve real world classification problems? *The journal of machine learning research* 15, 1 (2014), 3133–3181.

[19] Ijaz Ul Haq, Khan Muhammad, Amin Ullah, and Sung Wook Baik. 2019. DeepStar: Detecting starring characters in movies. *IEEE Access* 7 (2019), 9265–9272.

[20] Abdalraouf Hassan and Ausif Mahmood. 2018. Convolutional recurrent deep learning model for sentence classification. *Ieee Access* 6 (2018), 13949–13957.

[21] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. 2016. Deep residual learning for image recognition. In *Proceedings of the IEEE conference on computer vision and pattern recognition*. 770–778.

[22] Pedro Javier Herrera, José Dorado, and Ángela Ribeiro. 2014. A novel approach for weed type classification based on shape descriptors and a fuzzy decision-making method. *Sensors* 14, 8 (2014), 15304–15324.

[23] Geoffrey E Hinton, Simon Osindero, and Yee-Whye Teh. 2006. A fast learning algorithm for deep belief nets. *Neural computation* 18, 7 (2006), 1527–1554.

[24] Murhaf Hossari, Soumyabrata Dev, Matthew Nicholson, Killian McCabe, Atul Nautiyal, Clare Conran, Jian Tang, Wei Xu, and François Pitié. 2018. ADNet: A deep network for detecting adverts. *arXiv preprint arXiv:1811.04115* (2018).

[25] Andrew G Howard, Menglong Zhu, Bo Chen, Dmitry Kalenichenko, Weijun Wang, Tobias Weyand, Marco Andreetto, and Hartwig Adam. 2017. Mobilenets: Efficient convolutional neural networks for mobile vision applications. *arXiv preprint arXiv:1704.04861* (2017).

[26] Linqi Huang, Jun Li, Hong Hao, and Xibing Li. 2018. Micro-seismic event detection and location in underground mines by using Convolutional Neural Networks (CNN) and deep learning. *Tunnelling and Underground Space Technology* 81 (2018), 265–276.

[27] Yangqing Jia, Evan Shelhamer, Jeff Donahue, Sergey Karayev, Jonathan Long, Ross Girshick, Sergio Guadarrama, and Trevor Darrell. 2014. Caffe: Convolutional architecture for fast feature embedding. In *Proceedings of the 22nd ACM international conference on Multimedia*. 675–678.

[28] Pishtiwan HS Kalmet, Sebastian Sanduleanu, Sergey Primakov, Guangyao Wu, Arthur Jochems, Turkey Refaee, Abdalla Ibrahim, Luca v Hulst, Philippe Lambin, and Martijn Poeze. 2020. Deep learning in fracture detection: a narrative review. *Acta orthopaedica* 91, 2 (2020), 215–220.

[29] Andreas Kamilaris and Francesc X Prenafeta-Boldú. 2018. Deep learning in agriculture: A survey. *Computers and electronics in agriculture* 147 (2018), 70–90.

[30] Aydin Kaya, Ali Seydi Keceli, Cagatay Catal, Hamdi Yalin Yalic, Huseyin Temucin, and Bedir Tekinerdogan. 2019. Analysis of transfer learning for deep neural network based plant classification models. *Computers and electronics in agriculture* 158 (2019), 20–29.

[31] Zahra Kazemi and Houman Zarrabi. 2017. Using deep networks for fraud detection in the credit card transactions. In *2017 IEEE 4th International conference on knowledge-based engineering and innovation (KBEI)*. IEEE, 0630–0633.

[32] UA Khan, N Ejaz, Miguel A Martínez-del Amor, and Heiko Sparenberg. 2017. Movies tags extraction using deep learning. In *2017 14th IEEE International Conference on Advanced Video and Signal Based Surveillance (AVSS)*. IEEE, 1–6.
[33] Hugo Larochelle and Yoshua Bengio. 2008. Classification using discriminative restricted Boltzmann machines. In *Proceedings of the 25th international conference on Machine learning*. 536–543.
[34] Weibo Liu, Zidong Wang, Xiaohui Liu, Nianyin Zeng, Yurong Liu, and Fuad E Alsaadi. 2017. A survey of deep neural network architectures and their applications. *Neurocomputing* 234 (2017), 11–26.
[35] Jeffrey Lund and Yiu-Kai Ng. 2018. Movie recommendations using the deep learning approach. In *2018 IEEE international conference on information reuse and integration (IRI)*. IEEE, 47–54.
[36] Xiaoqiang Ma, Tai Yao, Menglan Hu, Yan Dong, Wei Liu, Fangxin Wang, and Jiangchuan Liu. 2019. A survey on deep learning empowered IoT applications. *IEEE Access* 7 (2019), 181721–181732.
[37] NS Manikandan and K Ganesan. 2019. Deep Learning Based Automatic Video Annotation Tool for Self-Driving Car. *arXiv preprint arXiv:1904.12618* (2019).
[38] Gary Marcus. 2018. Deep learning: A critical appraisal. *arXiv preprint arXiv:1801.00631* (2018).
[39] Volodymyr Mnih, Hugo Larochelle, and Geoffrey E Hinton. 2012. Conditional restricted boltzmann machines for structured output prediction. *arXiv preprint arXiv:1202.3748* (2012).
[40] Krishna Modi and Reshma Dayma. 2017. Review on fraud detection methods in credit card transactions. In *2017 International Conference on Intelligent Computing and Control (I2C2)*. IEEE, 1–5.
[41] Mehdi Mohammadi, Ala Al-Fuqaha, Sameh Sorour, and Mohsen Guizani. 2018. Deep learning for IoT big data and streaming analytics: A survey. *IEEE Communications Surveys & Tutorials* 20, 4 (2018), 2923–2960.
[42] Ruihui Mu and Xiaoqin Zeng. 2019. A review of deep learning research. *KSII Transactions on Internet and Information Systems (TIIS)* 13, 4 (2019), 1738–1764.
[43] Ghulam Murtaza, Liyana Shuib, Ainuddin Wahid Abdul Wahab, Ghulam Mujtaba, Henry Friday Nweke, Mohammed Ali Al-garadi, Fariha Zulfiqar, Ghulam Raza, and Nor Aniza Azmi. 2020. Deep learning-based breast cancer classification through medical imaging modalities: state of the art and research challenges. *Artificial Intelligence Review* 53, 3 (2020), 1655–1720.
[44] M Deepika Nair, MS Sinta, and M Vidya. 2018. A study on various deep learning algorithms to diagnose Alzheimer's disease. In *International Conference on ISMAC in Computational Vision and Bio-Engineering*. Springer, 1705–1710.
[45] Sella Nevo, Vova Anisimov, Gal Elidan, Ran El-Yaniv, Pete Giencke, Yotam Gigi, Avinatan Hassidim, Zach Moshe, Mor Schlesinger, Guy Shalev, et al. 2019. ML for flood forecasting at scale. *arXiv preprint arXiv:1901.09583* (2019).
[46] Kuniaki Noda, Yuki Yamaguchi, Kazuhiro Nakadai, Hiroshi G Okuno, and Tetsuya Ogata. 2015. Audio-visual speech recognition using deep learning. *Applied Intelligence* 42, 4 (2015), 722–737.
[47] Saroj Kumar Pandey and Rekh Ram Janghel. 2019. Recent deep learning techniques, challenges and its applications for medical healthcare system: a review. *Neural Processing Letters* 50, 2 (2019), 1907–1935.
[48] Adam Paszke, Sam Gross, Soumith Chintala, Gregory Chanan, Edward Yang, Zachary DeVito, Zeming Lin, Alban Desmaison, Luca Antiga, and Adam Lerer. 2017. Automatic differentiation in pytorch. (2017).
[49] Thulasyammal Ramiah Pillai, Ibrahim Abaker Targio Hashem, Sarfraz Nawaz Brohi, Sukhminder Kaur, and Mohsen Marjani. 2018. Credit card fraud detection using deep learning technique. In *2018 Fourth International Conference on Advances in Computing, Communication & Automation (ICACCA)*. IEEE, 1–6.
[50] Samira Pouyanfar, Shu-Ching Chen, and Mei-Ling Shyu. 2017. An efficient deep residual-inception network for multimedia classification. In *2017 IEEE International Conference on Multimedia and Expo (ICME)*. IEEE, 373–378.
[51] Samira Pouyanfar, Saad Sadiq, Yilin Yan, Haiman Tian, Yudong Tao, Maria Presa Reyes, Mei-Ling Shyu, Shu-Ching Chen, and Sundaraja S Iyengar. 2018. A survey on deep learning: Algorithms, techniques, and applications. *ACM Computing Surveys (CSUR)* 51, 5 (2018), 1–36.
[52] Mark Purdy and Paul Daugherty. 2016. Why artificial intelligence is the future of growth, Accenture.
[53] Pranav Rajpurkar, Allison Park, Jeremy Irvin, Chris Chute, Michael Bereket, Domenico Mastrodicasa, Curtis P Langlotz, Matthew P Lungren, Andrew Y Ng, and Bhavik N Patel. 2020. AppendiXNet: deep learning for diagnosis of appendicitis from a small dataset of CT exams using video pretraining. *Scientific reports* 10, 1 (2020), 1–7.
[54] Sina Rashidian, Janos Hajagos, Richard Moffitt, Fusheng Wang, Xinyu Dong, Kayley Abell-Hart, Kimberly Noel, Rajarsi Gupta, Mathew Tharakan, Veena Lingam, et al. 2018. Disease phenotyping using deep learning: A diabetes case study. *arXiv preprint arXiv:1811.11818* (2018).
[55] Tausifa Jan Saleem and Mohammad Ahsan Chishti. 2019. Deep learning for Internet of Things data analytics. *Procedia computer science* 163 (2019), 381–390.
[56] Saptarshi Sengupta, Sanchita Basak, Pallabi Saikia, Sayak Paul, Vasilios Tsalavoutis, Frederick Atiah, Vadlamani Ravi, and Alan Peters. 2020. A review of deep learning with special emphasis on architectures, applications and recent trends. *Knowledge-Based Systems* 194 (2020), 105596.
[57] Ajay Shrestha and Ausif Mahmood. 2019. Review of deep learning algorithms and architectures. *IEEE Access* 7 (2019), 53040–53065.
[58] Pushkar Shukla, Tanu Gupta, Aradhya Saini, Priyanka Singh, and Raman Balasubramanian. 2017. A deep learning frame-work for recognizing developmental disorders. In *2017 IEEE Winter Conference on Applications of Computer Vision (WACV)*. IEEE, 705–714.
[59] Karen Simonyan and Andrew Zisserman. 2014. Very deep convolutional networks for large-scale image recognition. *arXiv preprint arXiv:1409.1556* (2014).
[60] Christian Szegedy, Wei Liu, Yangqing Jia, Pierre Sermanet, Scott Reed, Dragomir Anguelov, Dumitru Erhan, Vincent Vanhoucke, and Andrew Rabinovich. 2015. Going deeper with convolutions. In *Proceedings of the IEEE conference on computer vision and pattern recognition*. 1–9.
[61] Tuan A Tang, Lotfi Mhamdi, Des McLernon, Syed Ali Raza Zaidi, and Mounir Ghogho. 2018. Deep recurrent neural network for intrusion detection in sdn-based networks. In *2018 4th IEEE Conference on Network Softwarization and Workshops (NetSoft)*. IEEE, 202–206.
[62] Uchechi Ukaegbu, Lagouge Tartibu, Timothy Laseinde, Modestus Okwu, and Isaac Olayode. 2020. A deep learning algorithm for detection of potassium deficiency in a red grapevine and spraying actuation using a raspberry pi3. In *2020 International Conference on Artificial Intelligence, Big Data, Computing and Data Communication Systems (icABCD)*. IEEE, 1–6.
[63] UF Ukaegbu, LK Tartibu, and MO Okwu. [n.d.]. DEEP LEARNING HARDWARE ACCELERATORS FOR HIGH PERFORMANCE IN SMART AGRICULTURAL SYSTEMS: AN OVERVIEW. ([n. d.]).
[64] Uchechi F Ukaegbu, Lagouge K Tartibu, Modestus O Okwu, and Isaac O Olayode. 2021. Development of a Light-Weight Unmanned Aerial Vehicle for Precision Agriculture. *Sensors* 21, 13 (2021), 4417.
[65] Glen L Urban, Artem Timoshenko, Paramveer S Dhillon, and John R Hauser. 2019. Is deep learning a game changer for marketing analytics? (2019).
[66] Jiarui Wang, Ying Qin, Zhiyuan Peng, and Tan Lee. 2019. Child Speech Disorder Detection with Siamese Recurrent Network Using Speech Attribute Features.. In *INTERSPEECH*. 3885–3889.
[67] Yibo Wang and Wei Xu. 2018. Leveraging deep learning with LDA-based text analytics to detect automobile insurance fraud. *Decision Support Systems* 105 (2018), 87–95.

[68] Rogier R Wildeboer, Ruud JG van Sloun, Hessel Wijkstra, and Massimo Mischi. 2020. Artificial intelligence in multiparametric prostate cancer imaging with focus on deep-learning methods. *Computer methods and programs in biomedicine* 189 (2020), 105316.

[69] Tom Young, Devamanyu Hazarika, Soujanya Poria, and Erik Cambria. 2018. Recent trends in deep learning based natural language processing. *ieee Computational intelligenCe magazine* 13, 3 (2018), 55–75.

[70] Ye Yuan, Guangxu Xun, Kebin Jia, and Aidong Zhang. 2017. A multi-view deep learning method for epileptic seizure detection using short-time fourier transform. In *Proceedings of the 8th ACM International Conference on Bioinformatics, Computational Biology, and Health Informatics*. 213–222.

[71] Mohamad Zamini and Gholamali Montazer. 2018. Credit card fraud detection using autoencoder based clustering. In *2018 9th International Symposium on Telecommunications (IST)*. IEEE, 486–491.

[72] Bin Zhang, Kyung-Min Hong, and Yung C Shin. 2020. Deep-learning-based porosity monitoring of laser welding process. *Manufacturing Letters* 23 (2020), 62–66.

[73] Jianjing Zhang, Peng Wang, Ruqiang Yan, and Robert X Gao. 2018. Deep learning for improved system remaining life prediction. *Procedia Cirp* 72 (2018), 1033–1038.

[74] Lei Zhang, Shuai Wang, and Bing Liu. 2018. Deep learning for sentiment analysis: A survey. *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery* 8, 4 (2018), e1253.

[75] Xinwei Zhang, Yaoci Han, Wei Xu, and Qili Wang. 2019. HOBA: A novel feature engineering methodology for credit card fraud detection with a deep learning architecture. *Information Sciences* (2019).

[76] Min Zhou, Yong Chen, Dexiang Wang, Yanping Xu, Weiwu Yao, Jingwen Huang, Xiaoyan Jin, Zilai Pan, Jingwen Tan, Lan Wang, et al. 2020. Improved deep learning model for differentiating novel coronavirus pneumonia and influenza pneumonia. *medRxiv* (2020).